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Trait Reduction in Chickpea (*Cicer arietinum* L.) Germplasm through Principal Component Analysis

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ABSTRACT

Keywords

Cicer arietinum L., Variability, Genetic Diversity, Principal Component, Eigenvalue

Article Info

Received: 15 June 2025 Accepted: 28 July 2025 Available Online: 10 August 2025 Enhancing chickpea (Cicer arietinum L.) seed production can be achieved by selecting superior genotypes according to various yield and yield component characteristics. Yield is a multidimensional feature that is controlled by several circumstances; thus, principal component analysis, a well-established method, was used to discover and limit the number of characteristics necessary for effective selection. As a result, this experiment was conducted to analyze the genetic diversity of chickpea genotypes. The study involved 81 chickpea germplasm lines and 15 check varieties, totalling 96, assessed through an augmented block design with four blocks. Each experimental unit consisted of two rows per genotype, each 2 meters in length, with a 0.5meter gap between rows and plants spaced 30 × 10 cm apart. Standard procedures were used to obtain data on 10 quantitative traits for every genotype. Among the ten principal components (PCs) analyzed, only three had eigenvalues exceeding 1.0, accounting for approximately 63.97% of the variability. PC 1 accounted for the largest portion of variability at 26.39%. This was followed by PC 2, which explained 21.79% of the variability with an eigenvalue of 2.17, and PC 3, which accounted for 15.79% with an eigenvalue of 1.57. The first three PCs—days to 50% pod setting, days to 50% flowering, and days to maturity—accounted for 63.97% of the overall variation and explained the characteristics. Genotypes frequently appearing in more PCs included ICC-16534, ICC-6816, ICC-12726, and CSJ-515. The current study revealed that chickpea germplasm exhibited significant genetic diversity across most of the traits examined.

Introduction

Chickpea (*Cicer arietinum* L.) (2n=2X=16), belonging to the subfamily Papilionaceae within the family Leguminosae, is a notable and unique food legume (Jain

et al., 2022). It is widely grown around the world and is considered the second most significant grain legume crop, following dry beans, in terms of global planting area. Chickpeas play a vital role in farming within dry and semi-dry areas and are also successfully cultivated in

winter crop rotations alongside cotton and maize in regions with temperate climates. However, warm and rainy climatic circumstances make Ascochyta blight a significant obstacle to winter-sown chickpea output, leading to considerable yield losses (Ton, 2023). Ensuring food and nutritional security is both economically and ecologically vital, particularly in climates subject to variability. This crop accounts for approximately 12 percent of pulse production worldwide (Mallu et al., 2015). Beyond its nutritional benefits, chickpea enhances soil fertility via symbiotic nitrogen fixation. Lately, chickpea cultivation has expanded to over 50 countries worldwide (Tsehaye et al., 2020). In India, chickpea production is projected to decline by 198 thousand metric tonnes (KMT) to 11.337 million metric tonnes (MMT) by 2025 (The Ministry of Agriculture and Farmers Welfare, 2024). Although states such as Madhya Pradesh, Andhra Pradesh, Maharashtra, and Karnataka have increased their chickpea cultivation areas, the growth of irrigated wheat farming has led to a notable decrease in chickpea cultivation in areas such as Punjab, Haryana, Uttar Pradesh, and Bihar (Arya et al., 2019).

Due to a limited genetic foundation and a variety of biotic and abiotic stressors, chickpea production potential has been severely curtailed. One of the main causes of the drop in chickpea yields per unit area is the limited genetic base and the lack of commercial cultivars with high yields. According to Agrawal et al., (2018), the majority of commercial chickpea cultivars are vulnerable to climate change and show little tolerance for a variety of environmental conditions. Individual variability is necessary for a species to survive in the wild and is a requirement for crop genetic modification initiatives to be effective (Singh et al., 2021). A primary obstacle to utilizing these cultivars has been the lack of knowledge regarding key economic traits (Gaur et al., 2012). Breeders must prioritize adaptation in varietal development initiatives to achieve sustainable agronomic benefits. Enhancing chickpea yield can be accomplished by selecting superior genotypes directly associated with seed yield. Breeding programs can use these genotypes just to increase grain yield. Since yield is a complicated characteristic that is impacted by a variety of environmental factors, principal component analysis, or PCA, has been developed. To cut down on the number of traits needed for effective selection, PCA finds and ranks the most relevant qualities.

Modern data analysis relies heavily on PCA, a simple, non-parametric method for extracting relevant

information from mixed datasets. To uncover the sometimes-concealed simplified structure that frequently underpins complicated data collection, PCA offers a path for reducing it to a lower dimension with the least amount of work. It preserves the majority of the dataset's variety while lowering the dimensionality of the data. PCA achieves this reduction by employing a small number of components to find the principal components or directions along which the data variation is maximum; A relatively small amount of numbers, as opposed to values for thousands of variables, can be used to represent each sample. Therefore, measuring the importance of each dimension for describing the variability of a dataset is PCA's primary benefit. Principal components, or a (lower) number of uncorrelated variables, are created by converting several (possibly) linked variables via a mathematical method (Muniraja et al., 2011).

Materials and Methods

Using principal component analysis, this study was conducted in Rabi 2024–2025 at the Student Inspection Farm, Department of Genetics and Plant Breeding, Chandra Shekhar Azad University of Agriculture and Technology, Kanpur, Uttar Pradesh, to evaluate superior chickpea genotypes.

The materials used in the experiment included 96 distinct genotypes of chickpeas, 15 of which were check varieties (Table 1), evaluated for ten quantitative traits, and sown augmented block design consisting of four blocks. The recommended packages and practices required for healthy crops were also included. The samples were from Hyderabad's International Crop Research Institute for Semi-Arid Tropics (ICRISAT). Two 2.0-meter rows were planted in each block, separated by 30 cm between rows and 8-10 cm between plants. Six quantitative characteristics were documented: days to 50% flowering (DF 50%), days to 50% pod setting (DPS 50%), days to maturity (DM), plant height (PH) (cm), number of primary branches per plant (NPB), number of secondary branches per plant (NPB), number of pods per plant (NPD/P), number of seeds per pod (NSD/PD), 100 seed weight (100 SW), and seed yield per plant (SY/P).

The bulk of the information in a large set can be retained when a large number of variables are reduced to a small set using the widely used PCA dimension reduction technique (Massay, 1965; Jolliffe, 1986). Thus, before beginning a hybridization program to create better

hybrids in chickpeas, the current study used principal component analysis to assess chickpea germplasm in order to find and rank important traits and genotypes. A statistical tool for principal component analysis is the factoextra package in R Studio (Kassambara and Mundt, 2020).

Results and Discussion

According to the findings of the basic descriptive statistics for the ten quantitative variables, a significant amount of variation was observed among the chickpea genotypes under investigation (Table 2).

Principal component analysis is one basic non-parametric technique that can be used to extract relevant information from mixed datasets. Principal Component Analysis (PCA) is a popular technique for dimension reduction, as noted by Massay (1965) and Jolliffe (2002). It successfully reduces a sizable collection of variables into a more manageable set while preserving the majority of the information found in the original data.

The current study aimed to assess chickpea genotypes to pinpoint and rank significant traits and genotypes using principal component analysis (PCA) before starting a hybridization program to create improved chickpea crosses. A statistical technique called principal component analysis uses an orthogonal transformation to convert a collection of observations of possibly correlated variables into principal components, which are sets of values of linearly uncorrelated variables. There are as many primary components as there are original variables, or fewer. Each consecutive component in this transformation has the highest variance while being orthogonal to the preceding components, with the first principal component capturing the maximum variance (i.e., explaining as much variability in the data as feasible). An uncorrelated orthogonal basis set is formed by the resultant vectors. Since the principal components are eigenvectors of the symmetric covariance matrix, they are orthogonal (Kumar et al., 2019).

In the present investigation, ten quantitative chickpea traits were subjected to PCA. Only three PCs out of ten had variability of roughly 63.97% and more than 1.0 eigenvalue (Table 3 and Fig. 1). Consequently, these three PCs received the attention they deserved in the current study. The genotypes for the characteristics under investigation were next in line, with PC1 explaining a total variation of 26.39% with an eigenvalue of 2.63.

Table 2 lists the two PCs that contributed the most to the overall variation: PC 1 and PC 2. PC 1 explained the greatest percentage of overall variability in the collection of all variables, whereas the other components explained decreasing percentages of variation. PC 1 demonstrated the most variability at 26.39 %. This was followed by PC 2 (21.79%) with an eigenvalue of 2.17, and PC 3 (15.79%) with an eigenvalue of 1.57. The findings above indicate that yield-contributing features varied the most in PC1, followed by PC2 and PC3. PCA aims to identify the fewest components that account for the greatest amount of variability among all components. In addition, the germplasm was ranked according to the PC scores. Malik *et al.*, (2014) and Rajani *et al.*, (2020) had similar outcomes.

The results also indicated that in PC1 (fig. 2 and Table 3), the number of secondary branches per plant (0.437), number of primary branches per plant (0.426), seed yield per plant (0.433), 100 seed weight (0.330), days to 50% pod setting (0.327), days to 50% flowering (0.280), number of seeds per pod (0.221), days to maturity (0.207), and number of pods per plant (0.193) had the most significant positive values, whereas plant height (-0.128) showed a negative value. Days to 50% blooming (0.495), days to 50% pod setting (0.489), and days to maturity (0.465) showed the highest positive values in PC 2, but all other features showed negative loadings. Positive contributions of days to 50% pod set and days to 50% blooming (0.495) were found in the third component. Akande (2007); Ojo et al., (2012); Miladinovic et al., (2006); Shivwanshi and Babbar (2017) and Amrita et al., (2014) corroborated these findings in chickpeas. According to their findings, the first PC was associated with characteristics that define production, such as the number of pods per plant, whereas the second PC was primarily dominated by phenological aspects.

More than one positive-scoring genotype was discovered in more PCs ICC 227, ICC 15510, ICC 107, ICC 2720, ICC 14778, ICC 8195, ICC 6816, ICC 867, ICC 19165, ICC 7867, ICC 440, ICC -16534, ICC -6816, ICC -12726, JG-14, BG3043, WR315, JAKI9218, PHULE G 405, JG74, CSJ-515, ICC -7877, ICC -3582, ICC -12324, ICC -6874, ICC -11764, ICC -11284, ICC -12307, ICC -8318, ICC -13628, ICC -10399, ICC -12299, ICC -4841, ICC 10341, ICC 16903, ICC 1533, ICC 6279, ICC -13523, ICC -13187, ICC -1357, Pusa JG-16, JG-24, Kundan, SamridhiJG-16, HC-5, GNG-2207 and GL-13001 (table 4 and fig 3).

Table.1 List of Genotypes used under this study

S.	Genotype	S.	Genotype	S.	Genotype	S.	Genotype	S.	Genotype
No	Name	No	Name	No	Name	No	Name	No	Name
1	ICC 4418	21	ICC 3218	41	ICC 8350	61	ICC -10399	81	ICC -3582
2	ICC 14669	22	ICC 2072	42	ICC 138	62	ICC -12299	82	Pusa JG-16
3	ICC 7819	23	ICC 2507	43	ICC 4495	63	ICC -4841	83	JG-24
4	ICC 11897	24	ICC 10673	44	ICC 14815	64	ICC -16534	84	Kundan
5	ICC 14446	25	ICC 16374	45	ICC 14778	65	ICC -6816	85	Samridhi
6	ICC 7323	26	ICC 19100	46	ICC 8195	66	ICC -8318	86	JG-14
7	ICC 762	27	ICC 6279	47	ICC 6816	67	ICC -11498	87	BG3043
8	ICC 10393	28	ICC 4491	48	ICC 10466	68	ICC -11284	88	WR315
9	ICC 16903	29	ICC 15435	49	ICC 867	69	ICC -12307	89	JAKI9218
10	ICC 1883	30	ICC 6294	50	ICC 19165	70	ICC -14687	90	PHULE G 405
11	ICC 6513	31	ICC 11121	51	ICC 7867	71	ICC -12328	91	JG74
12	ICC 1915	32	ICC 5845	52	ICC 440	72	ICC -1194	92	CSJ-515
13	ICC 6806	33	ICC 14831	53	ICC 1431	73	ICC -6874	93	JG-16
14	ICC 1533	34	ICC 227	54	ICC 19164	74	ICC -11764	94	HC-5
15	ICC 11378	35	ICC 15510	55	ICC - 4918	75	ICC -637	95	GNG-2207
16	ICC 1161	36	ICC 107	56	ICC -7819	76	ICC -13077	96	GL-13001
17	ICC 7326	37	ICC 2720	57	ICC -13523	77	ICC -12324		
18	ICC 56610	38	ICC 16795	58	ICC -13187	78	ICC -12726		
19	ICC 5434	39	ICC 26911	59	ICC -1205	79	ICC -1357		
20	ICC 9137	40	ICC 10341	60	ICC -13628	80	ICC -7877		

Table.2 Basic Descriptive Statistics of 10 yield-related traits

	DF 50%	DPS 50%	DM	PH	NPB	NSB	NPD/P	NSD/PD	100 SW	SY/P
Mean	75.97	87.35	115.52	34.90	5.25	13.76	52.07	1.69	14.79	13.38
Variance	7.01	10.69	62.78	45.99	2.84	12.52	188.87	0.21	9.57	27.80
St. dev.	2.65	3.27	7.92	6.78	1.68	3.54	13.74	0.46	3.09	5.27

Figure.1 Screen plot constructed based on thirteen principal component and their eigenvalues

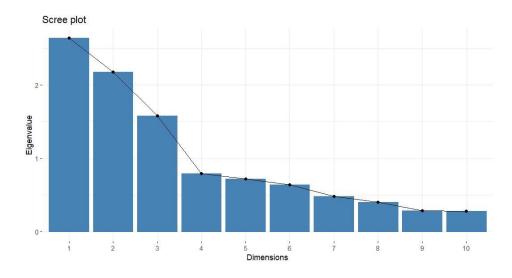


Table.3 Eigen value, Variability Contribution and Eigen vectors for the Principal Component Analysis in chickpea

Trait	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
DF 50%	0.280	0.495	0.005	0.009	-0.061	-0.151	-0.528	-0.114	0.423	0.423
DPS 50%	0.327	0.489	0.040	-0.024	0.090	0.034	-0.046	-0.241	-0.135	-0.751
DM	0.207	0.465	-0.259	0.151	0.308	-0.108	0.493	0.328	-0.298	0.324
PH	-0.128	-0.158	-0.588	-0.023	0.123	-0.667	-0.092	-0.363	-0.091	-0.066
NPB	0.426	-0.159	0.017	-0.482	-0.355	-0.304	-0.172	0.483	-0.278	-0.053
NSB	0.437	-0.117	-0.223	-0.064	-0.471	0.144	0.516	-0.380	0.283	0.094
NPD/P	0.193	-0.178	-0.510	0.575	-0.125	0.262	-0.284	0.362	0.085	-0.194
NSD/PD	0.221	-0.180	0.480	0.495	0.043	-0.548	0.197	0.120	0.267	-0.130
100 SW	0.330	-0.303	-0.102	-0.340	0.690	0.132	0.020	0.098	0.407	-0.065
SY/P	0.433	-0.283	0.187	0.222	0.193	0.143	-0.227	-0.397	-0.552	0.277
Eigenvalue	2.639	2.179	1.579	0.794	0.718	0.639	0.483	0.404	0.283	0.280
% of	26.39%	21.79%	15.79%	7.94%	7.18%	6.39%	4.83%	4.04%	2.83%	2.80%
Variance										
Cumulative	26.39%	48.18%	63.98%	71.91%	79.10%	85.49%	90.32%	94.36%	97.20%	100.00%
% of										
Variance										

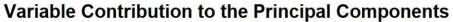
Table.4 PCA score for 96 genotypes of Chickpea

S. No.	Genot ype	PC 1	PC 2	PC 3	S. No.	Genot ype	PC 1	PC 2	PC 3	S. No.	Genot ype	PC 1	PC 2	PC 3	7 6	ICC - 13077	- 2.6 14	0.8 96	0.0 06
1	ICC 4418	- 1.2 95	- 0.6 13	- 0.5 60	26	ICC 19100	0.3 80	- 0.8 55	- 0.1 47	51	ICC 7867	3.7 43	- 1.1 19	- 0.0 80	7	ICC - 12324	0.3 51	2.6 91	1.5 64
2	ICC 14669	- 2.1 27	0.3 86	- 0.2 46	27	ICC 6279	0.0 05	1.0 28	1.1	52	ICC 440	2.1 10	- 2.2 76	0.3 69	7 8	ICC - 12726	1.6 64	3.6 78	1.7 14
3	ICC 7819	- 0.9 80	0.7 12	0.9 38	28	ICC 4491	0.3 98	3.0 20	1.2 82	53	ICC 1431	0.3 51	0.6 27	- 0.6 71	7 9	ICC - 1357	0.0 25	- 0.4 91	4.8 66
4	ICC 11897	- 0.6 56	- 0.7 90	0.1 16	29	ICC 15435	- 1.8 73	1.3 40	- 1.6 01	54	ICC 19164	0.7 43	- 0.2 16	- 0.4 49	8	ICC - 7877	- 0.8 04	1.7 65	0.7 11
5	ICC 14446	- 1.6 32	- 1.0 75	- 0.9 30	30	ICC 6294	0.0 47	- 1.0 41	- 0.0 17	55	ICC - 4918	- 0.5 66	0.5 44	1.0 51	8	ICC - 3582	0.1 35	1.8 58	0.2
6	ICC 7323	- 0.7 07	- 1.3 56	- 1.0 18	31	ICC 11121	- 0.8 37	- 0.4 42	- 2.6 57	56	ICC - 7819	- 1.7 21	- 1.1 35	- 1.6 66	8 2	Pusa JG-16	0.8 60	- 0.3 58	1.0 82
7	ICC 762	2.3 07	0.1 60	- 0.1 61	32	ICC 5845	- 0.3 80	- 0.6 15	- 1.5 06	57	ICC - 13523	0.6 73	- 0.6 48	1.4 66	8 3	JG-24	0.2 46	0.1 74	1.5 93
8	ICC 10393	- 0.3 85	- 0.9 21	- 0.4 40	33	ICC 14831	0.0	0.0 01	- 1.6 57	58	ICC - 13187	0.2 73	- 1.1 42	1.4 19	8 4	Kund an	0.1 44	- 0.6 64	1.4 53
9	ICC 16903	0.6	1.0	1.2 62	34	ICC 227	1.2 90	0.2 08	- 1.1	59	ICC - 1205	2.0	0.8 66	0.8 47	8 5	Samri dhi	0.2	- 0.9	1.8 84

Int.J.Curr.Microbiol.App.Sci (2025) 14(08): 176-185

		90	33						39			07					35	14	
10	ICC	-	-	-	35	ICC	2.3	0.6	-	60	ICC -	-	2.0	-	8	JG-14	1.4	-	1.3
	1883	0.7 18	0.3 66	0.8 84		15510	45	64	1.8 76		13628	1.3 95	18	1.2 98	6		15	0.4 30	16
11	ICC	-	-	-	36	ICC	3.8	-	-	61	ICC -	-	3.1	-	8	BG30	3.4	0.1	0.1
	6513	1.4 46	0.1 14	0.2 70		107	52	0.4 29	0.6 19		10399	1.4 80	74	0.0	7	43	87	17	55
12	ICC	-	0.2	-	37	ICC	2.8	-	-	62	ICC -	-	1.3	-	8	WR31	4.4	-	0.9
	1915	1.5 73	10	1.3 87		2720	14	1.0 86	0.2 94		12299	0.4 45	58	0.1 45	8	5	35	2.2 82	32
13	ICC	-	-	0.6	38	ICC	0.8	0.8	-	63	ICC -	-	3.3	0.3	8	JAKI	1.5	-	-
	6806	1.7 00	0.1 73	38		16795	48	70	2.0 28		4841	0.7 62	27	43	9	9218	75	0.4 95	0.0 92
14	ICC	-	-	1.6	39	ICC	0.5	0.8	-	64	ICC -	2.0	3.1	0.8	9	PHUL	1.3	1.0	-
	1533	1.6 14	1.4 98	31		26911	04	55	1.4 56		16534	91	58	41	0	E G 405	79	32	0.0 80
15	ICC	-	0.2	0.5	40	ICC	0.8	1.0	-	65	ICC -	1.2	3.5	2.0	9	JG74	1.0	-	0.4
	11378	2.2 09	96	52		10341	61	92	0.5 31		6816	74	31	69	1		30	0.3	46
16	ICC	-	-	-	41	ICC	0.6	-	-	66	ICC -	-	3.9	-	9	CSJ-	1.5	56 1.2	2.0
	1161	0.0	1.0	0.0		8350	31	0.7	0.6		8318	2.1	48	0.6	2	515	63	58	01
17	ICC	50	55	72	42	ICC	_	99	58	67	ICC -	37	0.7	36 0.8	9	JG-16	-	-	3.7
	7326	1.2	1.1	0.4		138	0.4	0.2	1.8		11498	1.9	72	92	3		1.5	2.0	25
18	ICC	60	33	71	43	ICC	0.6	0.0	13	68	ICC -	53	1.3	-	9	HC-5	82	46	2.9
	56610	1.5	0.0	0.4		4495	34	42	0.7		11284	25	06	0.6	4		3.5	4.4	48
19	ICC	04	40	54	44	ICC	0.7	0.8	39	69	ICC -	_	1.8	86	9	GNG-	58 -	93	2.7
17	5434	1.0	1.3	0.5		14815	30	45	0.0	0,	12307	0.8	63	0.6	5	2207	0.9	17	26
20	ICC	74 -	62	59	45	ICC	4.3	-	02	70	ICC -	41	0.8	93	9	GL-	0.5	_	1.3
	9137	1.2	0.3	0.5		14778	86	0.7	0.4	, 0	14687	1.7	63	1.2	6	13001	70	0.0	40
21	ICC	30	29	68 -	46	ICC	1.8	23	86 0.1	71	ICC -	71		98				84	
21	3218	0.8	1.3	0.8	40	8195	78	1.3	30	/ 1	12328	1.2	0.8	0.0					
22	ICC	94	61	06	47	ICC	3.9	55 -		72	ICC -	0.3	39 2.9	84					
22	2072	0.4	2.3	0.3	4/	6816	81	1.4	0.2	12	1194	29	90	0.2					
22	ICC	44	17	88	40	ICC	0.0	42	35	72	ICC		1.0	51					
23	ICC 2507	- 1.4	0.9	0.8	48	ICC 10466	0.9 94	0.3 19	- 1.4	73	ICC - 6874	0.2	1.0 22	1.0					
2.1		54	18	02	40				00	7.4		53		89					
24	ICC 10673	0.2	0.3	0.0	49	ICC 867	2.0 83	0.2	0.2	74	ICC - 11764	0.0	1.6 28	0.9 11					
		00	99					50	25			90	20						
25	ICC 16374	0.3	- 1.0	0.5	50	ICC 19165	1.3 13	0.0 68	1.3	75	ICC - 637	2.3	- 0.1	0.1 60					
	103/4	92	64	22		17103	13	-00	41		037	31	78	- 00					

Figure.2 Variable contribution of ten characters to Principal Component Analysis



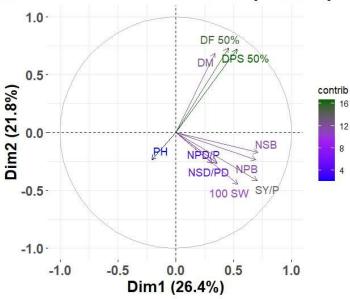
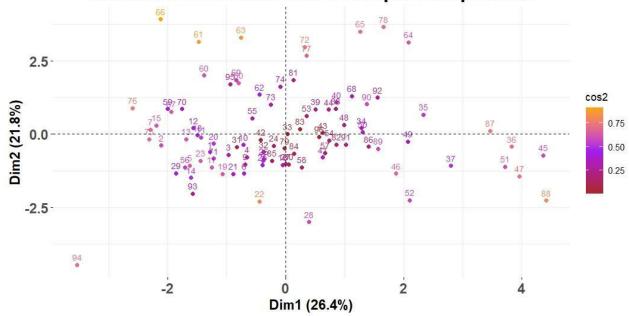


Figure.3 Individual Contribution to Principal Component Analysis

Individual Contribution to Principal Components



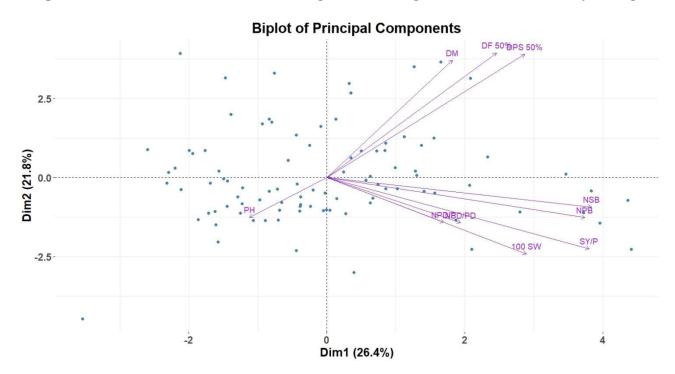


Figure.4 PCA Plot between 1st and 2nd component showing contribution of variability among

These genotypes can be used as ideotype breeding materials for selecting qualities linked to early maturity and seed yield, and they may also be used in breeding programs to increase seed yield (Rajani *et al.*, 2020; Jain *et al.*, 2023).

The distance of the variables to the PCs demonstrated their contributions to the genotypes (Fig. 4). The PCA biplot between PC1 and PC2 also showed that the most essential aspects contributing to genetic variability in the chickpea genotypes under study were the number of secondary branches per plant, seed yield per plant, number of primary branches per plant, 100 seed weight, days to 50% pod setting, days to 50% flowering, number of seeds per pod, days to maturity, and number of pods per plant.

The success of a breeding program aimed at improving chickpeas will depend more on the genotype selection made from the first three PCs (Mahmood *et al.*, 2018), and Malik *et al.*, (2014) published findings consistent with this study.

According to the PCA conducted in this study, the first three PCs—days to 50% pod setting, days to 50% flowering, days to maturity, and seed yield per plant—contributed 63.97% of the total divergence and traits.

These three PCs also significantly contributed to the overall variation in the yield. Therefore, it is possible to simultaneously select yielding traits in chickpeas using PCs 1, 2, and 3. These qualities can be considered for the continued development and progress of chickpeas.

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Author Contributions

Deepesh Singh Koshle: Conceived the original idea and designed the model and wrote the manuscript.; Majjiga Revanth Kumar: Designed the model and the computational framework and analysed the data.; Chandragupt Maurya: Done the formal analysis; Nikhil Kumar: Validated the draft manuscript; Amit Kumar: Corrected the data sets; Niharika Yduvanshi: Investigated the entire framework of the manuscript; Shivam Tripathi: Conceptual idea; Utkarsh Tiwari: Reviewed; Neha Yadav: Draft manuscript; Dr. Shweta: Reviewed the original manuscript.

Data Availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Conflict of Interest The authors declare no competing interests.

References

- Agrawal, T., Kumar, A., Kumar, S., Kumar, A., Kumar, M., & Satyendra, P. S. (2018). Assessment of genetic diversity in chickpea (*Cicer arietinum* L.) germplasm under normal sown condition of Bihar. *International Journal of Current Microbiology and Applied Science*, 7(4), 3552-3560.
 - https://doi.org/10.20546/ijcmas.2018.704.400
- Akande SR. Multivariate analysis of the genetic diversity of pigeon pea germplasm from south-west Nigeria. *Journal of Food Agriculture and Environment*, 2007; 5(1):224. ISSN: 1459-0255
- Amrita, B., Shrivastava, A., Bisen, R. And Mishra, S. (2014). Study of Principal Component Analyses for Yield Contributing Traits in Fixed Advanced Generations of Soybean (*Glycine max* (L.) Merrill). *Soybean Research*. Pp. 44 Soybean Research (Special Issue Number 2): 44-50: 2014
- Arya, M., Dwivedi, S., & Chaturvedi, S. K. (2019).

 Management of biotic stresses in chickpea exploiting host plant resistance. *International Journal of Agriculture, Environment and Biotechnology*, 12(2), 141-149.

 http://dx.doi.org/10.30954/0974-1712.06.2019.10
- Gaur, P.M., Jukanti, A.K., &Varshney, R.K. (2012).Impact of Genomic Technologies on Chickpea Breeding Strategies. *Agronomy*, 2, 199-221.
 - https://doi.org/10.3390/agronomy2030199
- Jain, S. K., Sharma, L. D., Gupta, K. C., Kumar, V., &

- Sharma, R. S. (2023). Principal component and genetic diversity analysis for seed yield and its related components in the genotypes of chickpea (*Cicer arietinum* L.). *Legume Research*, 46(9), 1174-1178. http://dx.doi.org/10.18805/LR-4489
- Jain, S. K., Sharma, L. D., Gupta, K. C., Sharma, R. S., Kumar, V., Singh, N.,... & Kumar, A. (2022). Trait associations and diversity analysis based on quantitative traits under moisture stress conditions in chickpea (*Cicer arietinum L.*). *Journal of Food Legumes*, 35(1), 3-10.
- Jolliffe, I. T. (1986). Principal component analysis and factor analysis. In *Principal component analysis* (pp. 115-128). New York, NY: Springer New York. https://doi.org/10.1007/978-3-642-04898-2 455
- Kassambara A, Mundt F (2020). factoextra: Extract and Visualize the Results of Multivariate Data Analyses. R package version 1.0.7.999, https://github.com/kassambara/factoextra.
- Kumar, A., Kumar, A., Ranjan, R., Kumar, S., Rajani, K., & Singh, P. (2019). Principal component analysis of Agro-morpho-genetic traits in Desi chickpea (*Cicer arietinum* L.). *SP*, 362-365.
- Kumari Rajani, A. K., Kumar, R. R., & Perween, S. Principal Component Analysis in Desi Chickpea (*Cicer arietinum* L.) under Normal Sown Condition of Bihar. *Current Journal of Applied Science and Technology*. 39(9): 75-80, 2020; ISSN: 2457-1024
- Mahmood, M. T., Ahmad, M., Ali, I., Hussain, M., Latif, A., & Zubrair, M. (2018). Evaluation of chickpea genotypes for genetic diversity through multivariate analysis. *Journal of Environmental and Agricultural Sciences*, 15(6), 11-17.
- Malik, S.R., Shabbir, G., Zubur, M., Iqbal, S.M. and Ali, A. (2014). Genetic diversity analysis of morphogenetic traits in Desi chickpea (*Cicer arietinum* L.). International Journal of Agriculture and Biology. 16: 956-960. : 1814–9596 13–562/2014/16–5–956–960
- Mallu, T. S., Mwangi, S. G., Nyende, A. B., Rao, N. V.
 P. R. G., Odeny, D. A., Rathore, A., & Kumar,
 A. 2014. Assessment of genetic variation and heritability of agronomic traits in chickpea (Cicer arietinum L). International Journal of Agronomy and Agricultural Research, 5(4), 76-88.
- Massay, W.F. (1965). Principal components regression in exploratory statistical research. *Journal of American Statistics Associations*. 60: 234-246.

- Miladinovic Jegor, Hideki Kurosaki, Joe W Burton, Milica Hrustic, Dragana Miladinovic. The adaptability of short-season soybean genotypes to varying longitudinal regions. *European journal of Agronomy*. 2006;25:243-9 https://doi.org/10.1016/j.eja.2006.05.007
- Muniraja, C., Satish, R.G., Raju, C. and Hart, M., 2011. Principal component analysis among genotypes of chickpea (*Cicer arietinum* L.). International Journal of Agricultural Sciences, 7(2), 382-386.
- Ojo, D.K., Ajayi, A.O. and Oduwaye, O.A. (2012). Genetic relationships among soybean accessions based on morphological and RAPD techniques. *Pertanika Journal of Tropical Agricultural Science*. 35: 237-48. ISSN: 1511-3701
- Shivwanshi, R. and Babbar, A. (2017). Principal Component Analysis of Chickpea (*Cicer arietinum* L.) Germplasm. *International Journal of Current Microbiology and Applied Sciences*. 6: 166-173.

https://doi.org/10.20546/ijcmas.2017.610.021

- Singh, R. K., Singh, C., Ambika, Chandana, B. S., Mahto, R. K., Patial, R.,... & Kumar, R. (2022). Exploring chickpea germplasm diversity for broadening the genetic base utilizing genomic resources. *Frontiers in Genetics*, *13*, 905771. https://doi.org/10.3389/fgene.2022.905771
- Ton, A. (2023). Multivariate analysis for agromorphological and cooking properties in chickpea (*Cicer arietinum* L.) germplasm. *Turkish Journal of Agriculture and Forestry*, 47(4), 590-601. https://doi.org/10.55730/1300-011X.3111
- Tsehaye, A., Fikre, A., & Bantayhu, M. (2020). Genetic variability and association analysis of Desi-type chickpea (*Cicer arietinum* L.) advanced lines under potential environment in North Gondar, Ethiopia. *Cogent Food & Agriculture*, 6(1), https://doi.org/10.1080/23311932.2020.1806668
- Welfare, F. (2024). Ministry of Agriculture and Farmers Welfare. *Government of India*, 4.

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